

AUTOMATED HAND-FOREARM ERGOMETER DATA
ACQUISITION AND ANALYSIS SYSTEM

by

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ABSTRACT

Handgrip contractions are a standard exercise modality to evaluate muscular system performance. Most conventional ergometer systems that collect handgrip contraction data are manually controlled, placing a burden on the researcher to guide subject activity while recording the resultant data. Further, post-processing tools for this type of experiment are not standardized within the domain, which requires investigators to process their data with multiple tool sets and often create custom tool sets for that purpose. This can make experimental data difficult to compare and correlate, even within the same research group.

This thesis presents updates to a hand-forearm ergometer system that automate the control and data-acquisition processes as well as provide a tool set to post process hand contraction data. The automated system utilizes a LabVIEW virtual instrument as the system centerpiece; it provides the subject/researcher interfaces and coordinates data acquisition from both traditional and new sensors. The tool set also incorporates a collection of MATLAB scripts that allow the investigator to post process these data in a standard way, such as automating the processes of noise floor removal, burst start/stop time identification, and mean/median frequency calculation in electromyograms (EMGs).

The tool set has proven to be a viable support resource for experimental studies performed by the Kansas State University Human Exercise Physiology lab that target muscle fatigue in human forearms. Initial data acquired during these tests indicate the viability of the system to acquire consistent and physiologically meaningful data while providing a usable tool set for follow-on data analyses.

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CHAPTER 1: INTRODUCTION

A. Motivation

The work described in this thesis was supported by the Kansas State University (KSU) Human Exercise Physiology Laboratory (KSU Department of Kinesiology) and the KSU Department of Electrical & Computer Engineering (ECE) with funding from the NASA Human Research Program – *Research and Technology Development to Support Crew Health and Performance in Space Exploration Missions* [1]. The program addresses research to improve astronaut health during space exploration. One focus of the KSU project is the detection of the onset of fatigue in astronaut musculature; in this case, forearm muscle fatigue while performing intense or long-duration hand-forearm tasks. The studies that motivated the technical work presented in this document focused on monitoring/predicting muscle fatigue in human forearms using a two-hand ergometer system. Inter-researcher variations posed a challenge in previous such investigations because all elements of the experiment were operator controlled. To improve data quality and experimental consistency, this work sought to automate the experimental process [2].

B. Traditional Hand-Forearm Ergometer Systems

Handgrip contractions are a standard means to evaluate the intact muscular system [3, 4] and mechanisms of fatigue [5]. Traditional hand-forearm ergometers allow a single limb to be exercised and usually require the subject to pull against a resistance created by suspended weights or a spring. This type of resistance often limits the researcher to testing the subject at a single work rate per session. During these sessions, the researcher must provide continual squeeze-hold-release prompts to the subject. Additionally, most of these systems rely on the researcher to manually acquire data and identify subject fatigue [6, 7]. Recent hand-forearm ergometer setups have employed automated, one-way data collection systems [8, 9], where adjustments can be made to moving pieces (e.g., for subject comfort), data collection parameters, and limited post-processing capabilities. However, these systems tend to be experimentally specific and do not offer the researcher a central interface to control data collection and processing [8].

C. Other Commercial Systems for Fatigue Assessment

Many off-the-shelf data collection systems exist for research use. Commercial wireless systems to acquire and process electromyograms (EMGs) include the following:

1. **Delsys Myomonitor Wireless EMG System** [10]

This EMG system is partially wireless. The product consists of a lightweight control box that can be hung from a subject's belt, where EMG sensors are hardwired into the control box. The data are then stored on a memory card and post-processed with EMGworks.

2. **zFlow Motion BTS FREEEMG 300 Wireless EMG System** [11]

This system contains wireless EMG probes that are small and compact. It holds enough memory for several hours of data storage. The system is also wireless (from the control box) and supports a full-size track radius.

3. **Myon 320 System** [12]

This system is similar to the zFlow product, but it comes with a post-processing tool set that offers integrated EMG, median/mean frequencies, intra-trial/inter-trial averages, etc..

4. **Delsys Trigno Wireless System** [13]

This system provides many of the same attributes as the zFlow and Myon products, except it is fully wireless. Each EMG sensor is packaged in a small compact unit with no protruding wires. Tri-axial accelerometers are also provided in each small package.

Real-time processing and post-processing systems include the following:

1. **LabVIEW** [14]

LabVIEW is a software environment “for graphical programming and unprecedented hardware integration for rapid designing” that allows one to create virtual instruments for data collection and analysis. This environment is easily learned and implemented by programmers and non-programmers alike.

2. **MATLAB** [15, 16]

“MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming... [It allows the user to]... analyze

data, develop algorithms, and create models and applications.” MATLAB is well-suited for EMG processing and display.

3. **Myon ProEMG** [12]

This software program is used in conjunction with the Myon 320 System. It allows the researcher to perform filtering, rectification, smoothing, frequency-based analysis, and many other EMG processing tasks.

Each of these systems alone cannot provide a researcher with all of the tools and flexibility needed to automate hand-forearm data gathering and EMG-based fatigue analysis. The project described in this thesis addressed this need by providing the means to prompt the subject, control the resistive elements of the ergometer, and collect data from both the EMG sensors and the off-the-shelf equipment that comprise the hand-forearm ergometer system.

CHAPTER 2: ORIGINAL ERGOMETER DESIGN

A. Overview and Functionality

The KSU Human Exercise Physiology Laboratory, with help from the KSU Electronics Design Laboratory (EDL) and the KSU Department of Mechanical & Nuclear Engineering, created a (two-hand) hand-forearm ergometer system. The system was built to allow for potentially multiple testing scenarios and designed to allow for data collection upgrades. The original system, depicted in Figure 2.1, was comprised of these elements:

1. Ergometer (handgrips and assembly)
2. Pressure cylinders and manual control box
3. Potentiometers and load cells
4. Digital metronome and stopwatch (not depicted)
5. Researcher interface

These items are discussed in the paragraphs that follow.

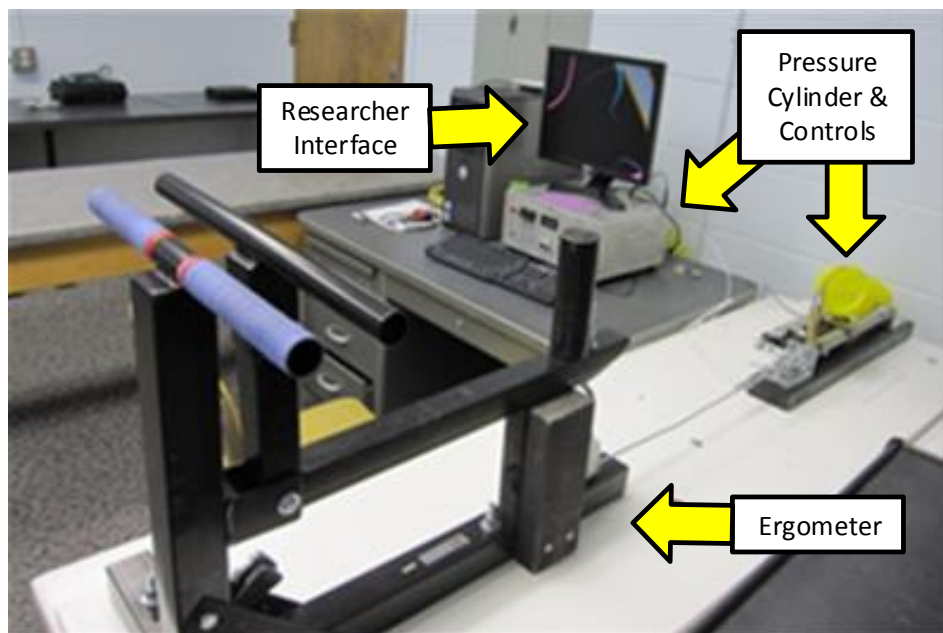


Figure 2.1 The original hand-forearm (handgrip) ergometer system.

The original ergometer design would normally be used for trials requiring a subject to squeeze the two bars of the ergometer together repeatedly until the end of the experiment or until

their hands and forearms reached the point of fatigue. An example of how a subject would position themselves to use the ergometer can be seen in Figure 2.2.



Figure 2.2 Demonstration of the hand-forearm ergometer system.

Two pressure cylinders (see Figure 2.1) had been added to the system to replace the traditional static weight (i.e., resistance) on a typical ergometer. The pressure cylinder control box is depicted in Figure 2.3. This modification allowed for both static (constant pressure) and ramp (linearly increasing pressure) exercise testing with subjects. The pressure in each cylinder is supplied by a standard pressure tank that holds a nitrogen gas mixture. The force required to squeeze the bars equates to the cylinder pressure, which can be raised or lowered by the researcher using a potentiometer dial on the front of the pressure control box. This allows the researcher to adjust the pressure to affect subject fatigue rate, as in a ramp testing procedure.

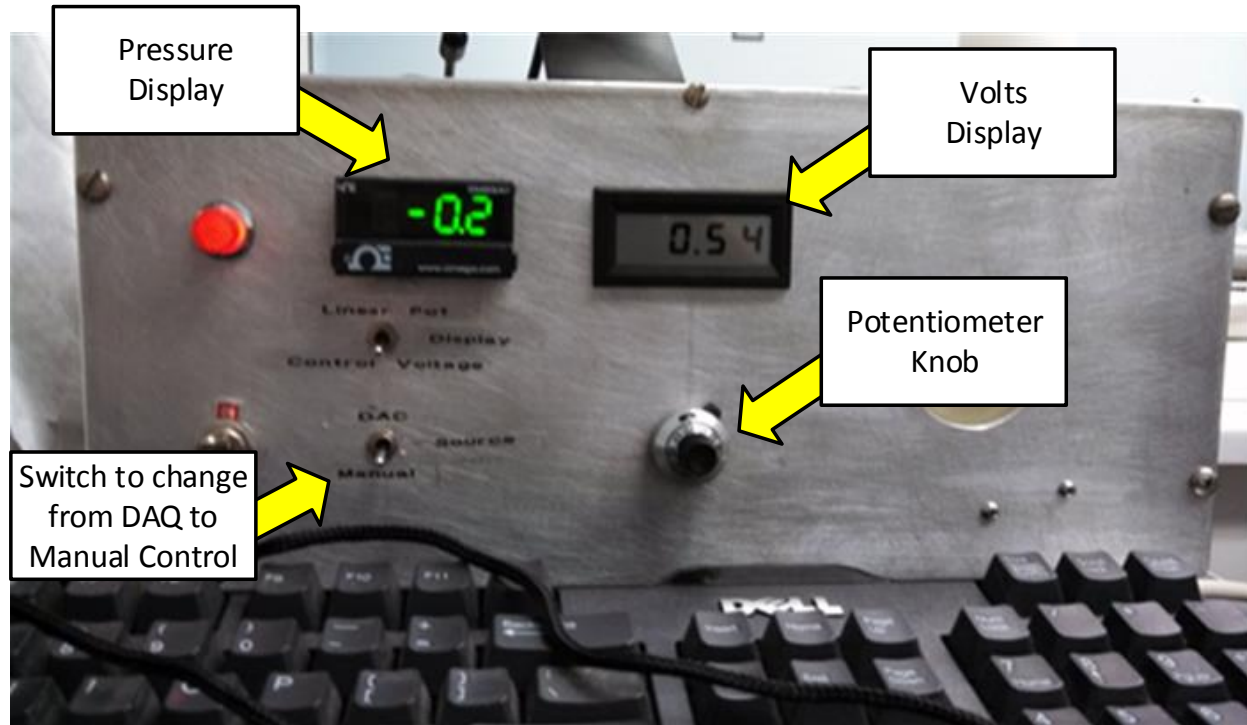


Figure 2.3 Front of the manual pressure control box.

An OMEGA LP801 linear potentiometer and a miniature tension/compression load cell (0 to 300 lbs; 0 to 1500 N) were also added to the pressure cylinder system to track force and displacement due to each hand contraction. These signals are digitized by two additional channels on a USB-6211 data acquisition (DAQ) card and sent to the researcher interface [14], where they are displayed and then stored in files for offline power calculations.

A digital metronome, with additional prompts from the researcher, would be used to pace each subject for the squeeze-hold-release process. The researcher would then use a stopwatch to measure time intervals that were manually recorded on a computer document or on a paper chart.

B. Necessary Upgrades

Several key upgrades were envisioned to improve the original system. These included a subject interface, a means to control certain ergometer parameters digitally via a researcher interface, and the ability to easily add additional sensors to the setup. Further requirements, if met, would make the tool set more useful in a practical:

1. All data need to be time-aligned and stored in a tab-spaced file for post processing.

2. Any added sensors must withstand the testing environment and not hinder the subject or researcher during the experiments.
3. The researcher interface must display data in a helpful manner and provide access to system controls/options and data storage options. Since requirements would change for each study, the interface must be reprogrammable using a method or programming language easily learned by non-programmers.
4. Post processing tool sets must be available to analyze data provided by the attached sensors. The algorithms must be easy to use and modify, and they need to be effective for all sample rates and procedures chosen by the researcher.

The following chapters discuss the upgrades implemented to accommodate these needs.

CHAPTER 3: ERGOMETER OVERVIEW AND FUNCTIONALITY

The overall goal for the updated hand-forearm ergometer system is to automate the process of gathering, storing, and analyzing data taken during hand-forearm ergometer studies. To accommodate the requirements discussed in Chapter 2, several upgrades were made to the system. Overall system improvements focused on consolidating system needs, automating the data acquisition process, and storing the resultant data electronically. These broad updates included the addition of contact sensors whose data are also streamed into the researcher interface, the capability to receive data from additional sensors customized to the needs of the data collection protocol (e.g., additional electromyogram (EMG) sensors attached to user forearms), the creation of LabVIEW-based subject/researcher interfaces (a.k.a., virtual instruments (VI)), automatic streaming of pressure cylinder data into the researcher interface, and the ability to control the pressure in the cylinders using the researcher interface. The sections that follow address these updates in more detail.

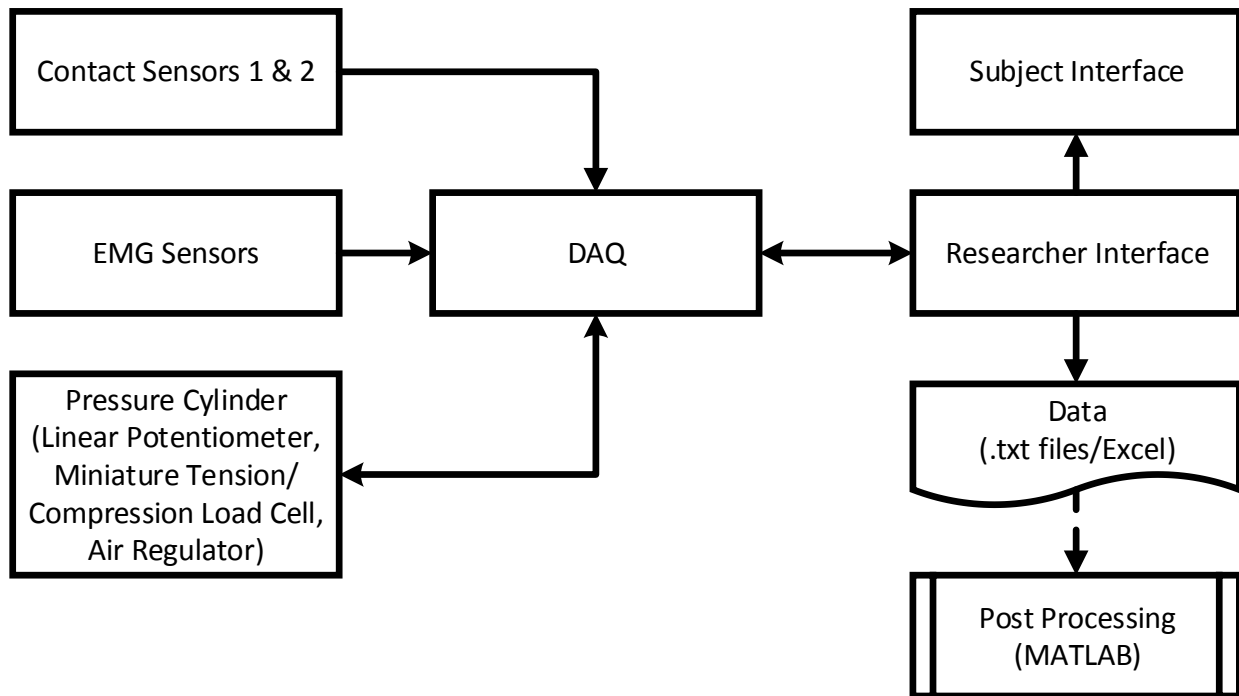


Figure 3.1 Hand-forearm ergometer data flow diagram.

A. Sensors

To improve the information available to the investigator, several sensors were added to the system (see Figure 3.2). To allow the researcher to monitor squeeze and release sequences, FSR402 0.5” flex sensors were added as contact sensors. Their thin profile, as discussed in the flex sensor data sheet [17] allows them to easily fit in small, tight locations. While this particular contact sensor does display more drift as compared to other contact sensors [18], the drift is not an issue when using them to take binary (open versus closed) readings.

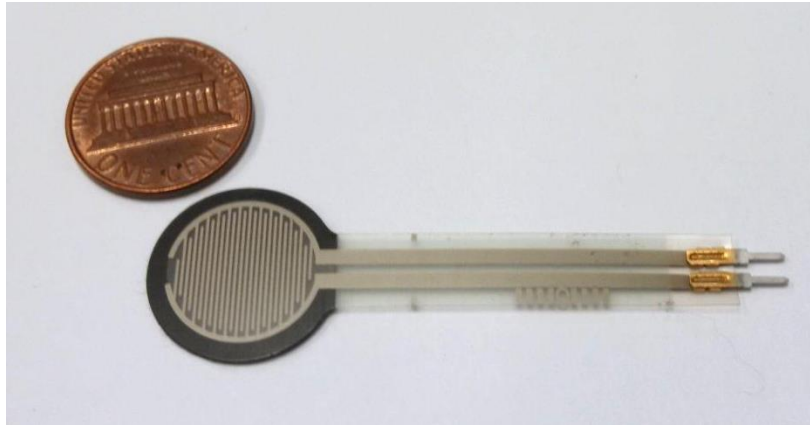


Figure 3.2 Image of a flex sensor used as a contact sensor.

The two FSR402 0.5” flex sensors were mounted to the hand ergometer: one between the two hand bars and the other between the support block and the lower bar, as indicated in Figure 3.3. The output voltages from their circuitry are monitored by two channels of a National Instruments (NI) USB-6211 DAQ card that offers sixteen 16-bit input channels.

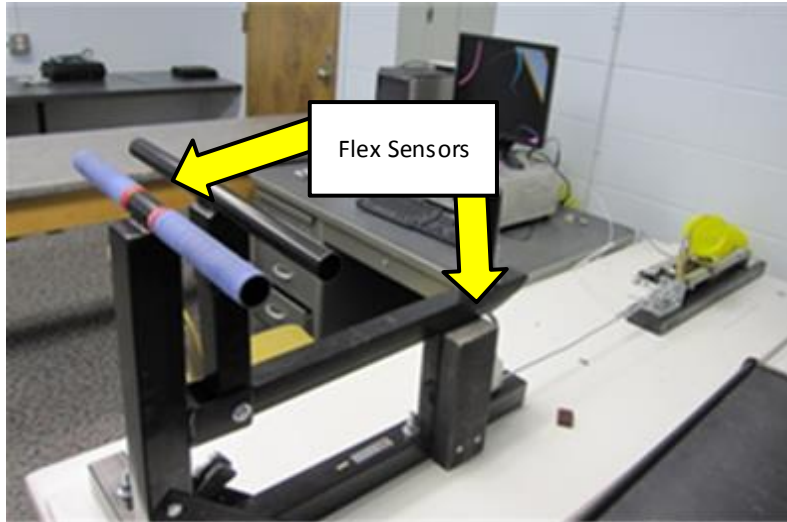


Figure 3.3 Flex sensor placement.

To create adequate sensitivity while still considering the maximum pressure that could be applied to the flex sensors, 100 k Ω pull-up resistors were used as in Figure 3.4.

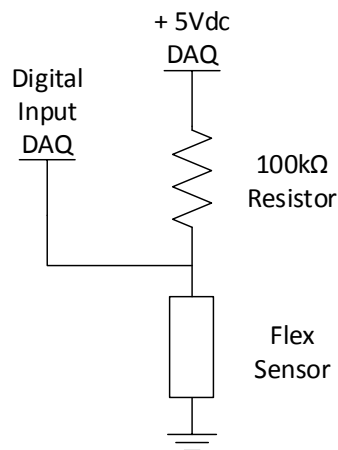


Figure 3.4 Pull-up resistor circuit for a Flex Sensor.

The result is a set of data streams whose binary nature indicates contact and non-contact states during the squeeze-hold-release process typical of a handgrip ergometer experiment. These on/off states are presented to the subject and researcher as green, red, and black indicators within the respective LabVIEW interfaces.

Additionally, EMG data sets were needed for these studies. For researcher ease of use, an off-the-shelf Delsys Trigno Wireless package (Figure 3.5) was added to the system. Delsys EMG data were then provided through the same NI USB-6211 DAQ board. Running the Delsys

data through the DAQ board ensured that the surface EMG data were time aligned with the other data streamed to the researcher interface.

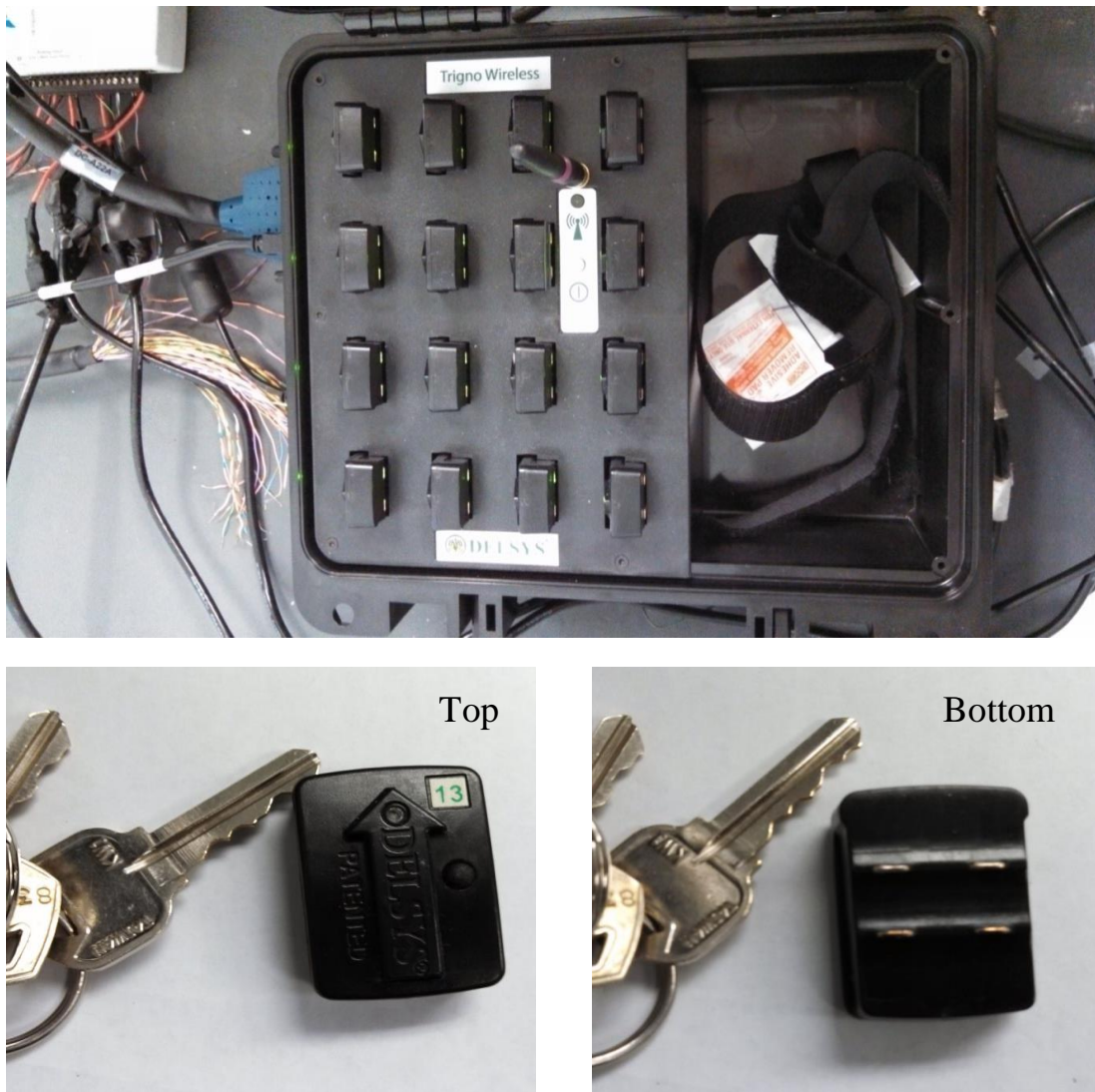


Figure 3.5 Delsys wireless EMG system used in the trials. The upper image displays the 16 individual wireless pods. The lower two images display top/bottom views of a single wireless pod that would be placed on a subject.

B. Researcher Interface

The researcher interface (Figure 3.6) is the central location for sending subject prompts and receiving sensor data. Its role is to provide a complete control, acquisition, and analysis interface that allows a researcher to perform any number of hand-forearm ergometer protocols. The

interface controls the audiovisual prompts for the subject and controls the pressure in the cylinders as it collects, displays, and stores sensor data.

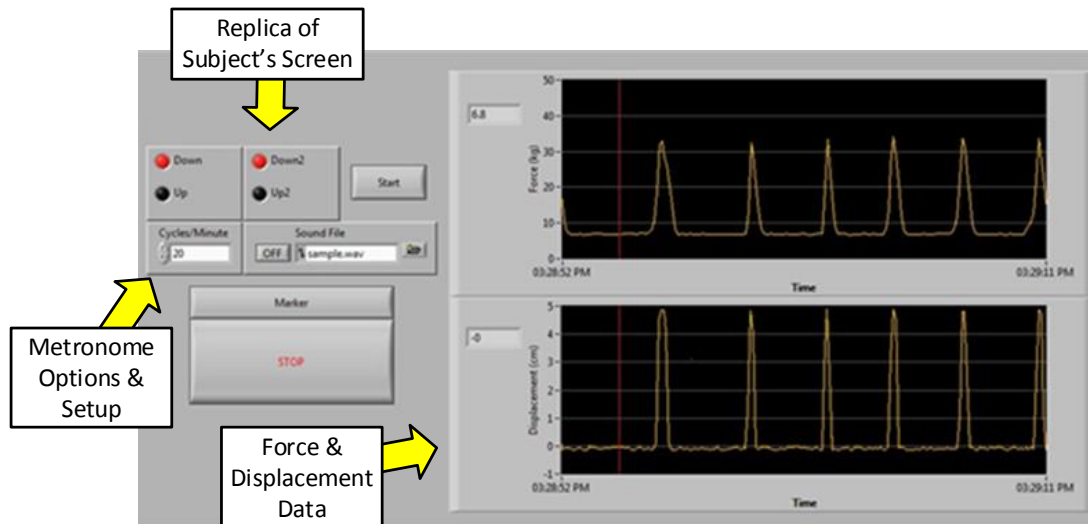


Figure 3.6 Researcher interface created in LabVIEW.

The top left section of the researcher interface displays a replica of the subject interface. This allows for a physical setup where the researcher does not have to be able to see the subject or the subject's screen to monitor the subject's movements. With this setup, the investigator can use the flex sensor data to determine the status of the subject's actions (e.g., a failure when the squeeze sensor no longer experiences contact). In the original, manually controlled ergometer, this type of information would be difficult to gather. A Cycles/Minute indicator box allows the investigator to choose the rate of the audiovisual prompts. This value is purposefully hidden from the subject to allow the investigator to be able to increase or decrease the value without allowing the subject to knowledgeably bias their movements. A box to the right of the Cycles/Minute indicator box allows the researcher to choose the sound file for the metronome. Different subjects hear different types of sounds with variable clarity. The sound file box only accepts windows media file extensions.

The researcher interface also displays the force and displacement readings obtained from the sensors connected to the pressure cylinders. (The graphs displayed on the right side of the interface are example data acquired from the force and displacement sensors.) These real time data are also recorded to text files for further evaluation. A contradiction between the contact sensor data and the pressure cylinder data can also provide the researcher with information

regarding the subject's ability to complete the experiment/task at hand (e.g., the subject might squeeze and generate a displacement signal but not achieve full sensor contact).

C. Subject Interface

In many research settings it is important to shield the subject from the data and from the equipment settings to keep the subject from influencing the results. A separate subject interface was created to meet this need. The subject interface (Figure 3.7) provides visual and audible prompts to the subject and is fully controlled by the researcher interface. The subject interface contains two columns of indicator lights. The lights in the left column prompt the user to either squeeze or release the ergometer bar (i.e., an ideal movement pattern for the subject). State changes in this column are accompanied by an audible sound, much like a metronome. The lights in the right column provide feedback regarding the actual movements performed by the subject. A red light indicates that the subject has released the bar: the ergometer is in the 'Down' position. A green light indicates that the subject is squeezing the ergometer handles: the ergometer is in the 'Up' position. This feedback helps the subject synchronize their movements with the cadence set by the researcher via the left column of lights. It also helps the subject and researcher ensure a proper squeeze/release pattern for the ergometer bars.

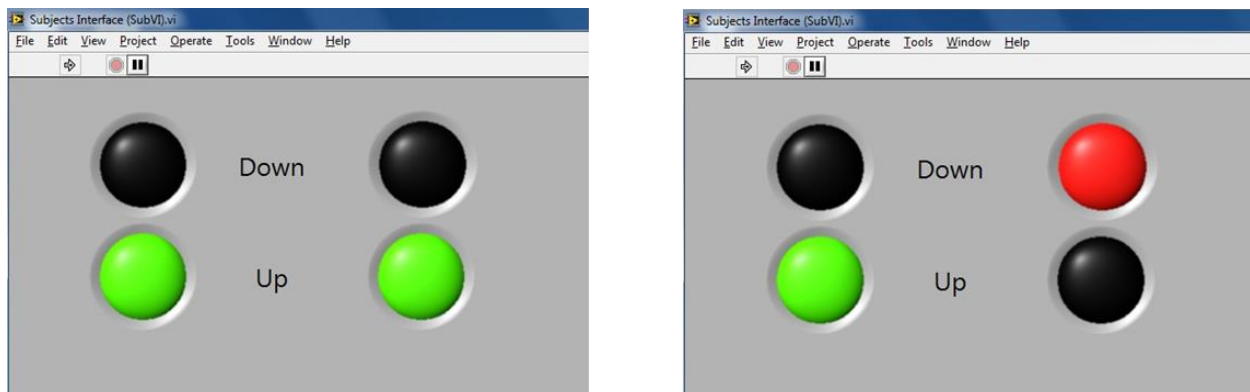


Figure 3.7 Subject interface created in LabVIEW. The left image depicts correct subject movement, whereas the right image depicts incorrect subject movement.

D. Addition of Pressure Controls

As discussed previously, the original system used a potentiometer knob as the control for the pressure in the cylinders. When using the potentiometer knob, the researcher would have to wait for the voltage to settle before the pressure in the cylinder would become stabilized. This made it difficult for the investigator to quickly dial to a specific value. To streamline the controls further, a digitized pressure cylinder control was created. Creating the control was easily accomplished, because the EDL had configured the control box to be easily switched from manual control (potentiometer knob) to DAQ (or other digital interface) control through an analog signal. To control the voltage value through the researcher interface, a current amplifier was needed to supply the current to the air regulator in the control box (the DAQ board analog outputs could only provide a maximum current of 2 mA [19]). A transition to an NI myDAQ board addressed this problem. The voltage is regulated through a set of analog outputs from the myDAQ, and a simple current amplifier circuit was designed (using a 741 op-amp in a unity gain buffer connected to the power supplies on the myDAQ) to create enough power to feed the pressure regulator.

Figure 3.8 displays the digital control on the researcher interface that allows the investigator to set more precise and stable values for the cylinder pressure. Additionally, the easily modified LabVIEW code allows the researcher to modify the pressures in terms of multiple desired units: force, pressure, or voltage output to the air regulator in the control box. If the researcher needs to override the DAQ board, a toggle switch on the front of the control box allows the researcher to toggle between the interface and the manual potentiometer dial (Figure 3.9).

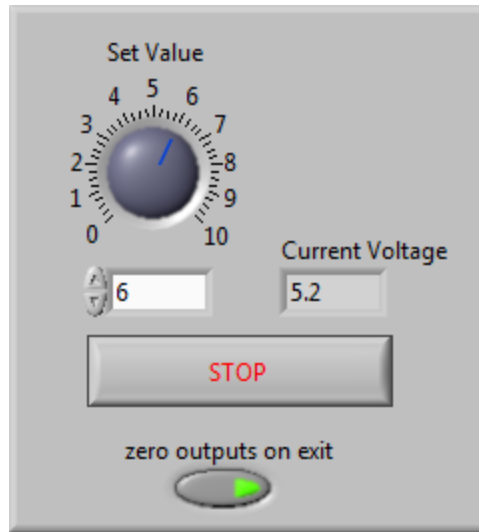


Figure 3.8 LabVIEW cylinder pressure control interface.

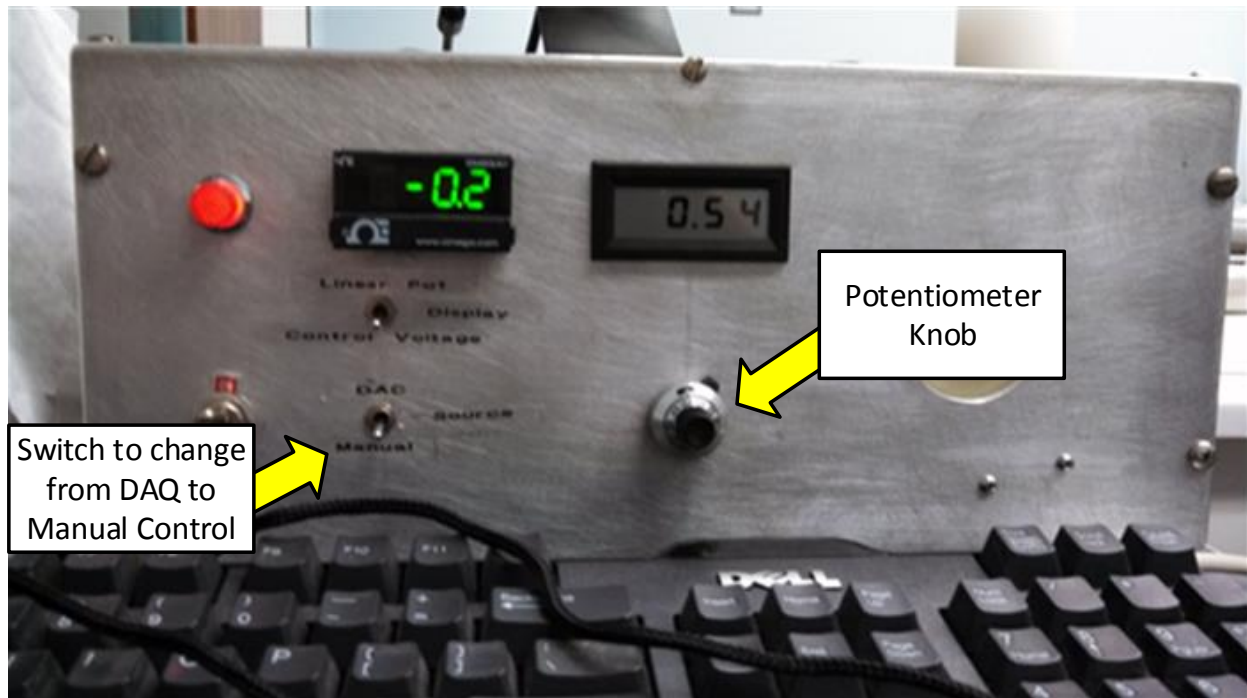


Figure 3.9 Front panel of the manual pressure control box. The right arrow identifies the switch to use the DAQ-controlled pressure cylinder interface versus the manual potentiometer knob. The left arrow identifies the pressure control potentiometer knob.

To further improve the system, an automated pressure increase interface was created (Figure 3.10). This interface allows the investigator to have the pressure automatically increase at a given interval. The investigator simply enters the start value, end (maximum) value,

increase (step) value, and time between steps (delay time). The interface also allows the investigator to set a countdown until exercise starts. The countdown provides the researcher and subjects time to coordinate their efforts and allows the system to stabilize the initial pressure value in the pressure tank. If the researcher decides that they do not want or need the countdown, a value of zero can be used and no countdown will occur.

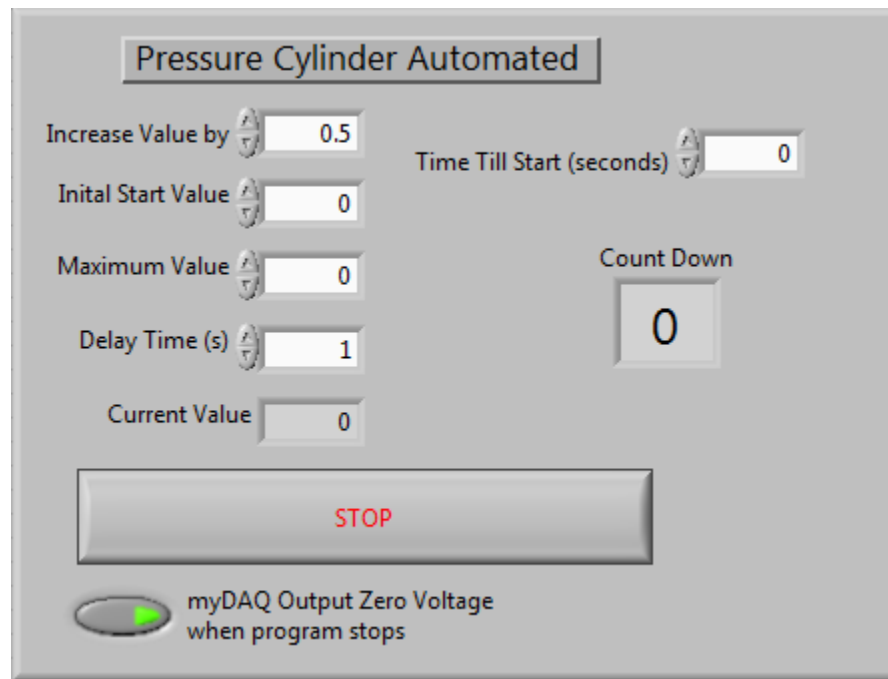


Figure 3.10 Automated ramp-up pressure cylinder LabVIEW interface.

E. Data Collection Capabilities

All sensor data are collected through the NI DAQ board. This allows the information to be time aligned when it reaches the researcher interface. The interface then disperse the data to three corresponding text files for post processing, as illustrated in Figure 3.11.

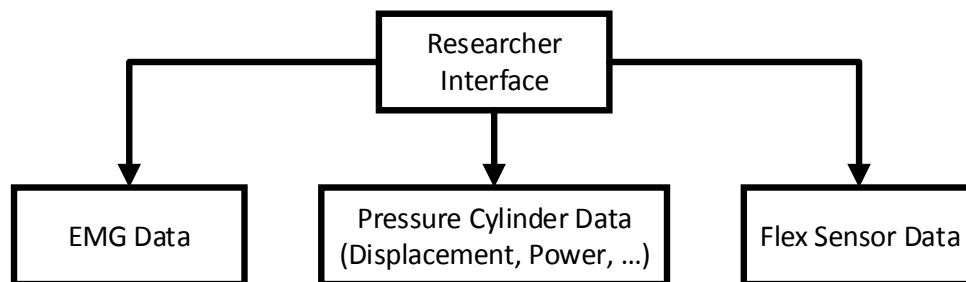
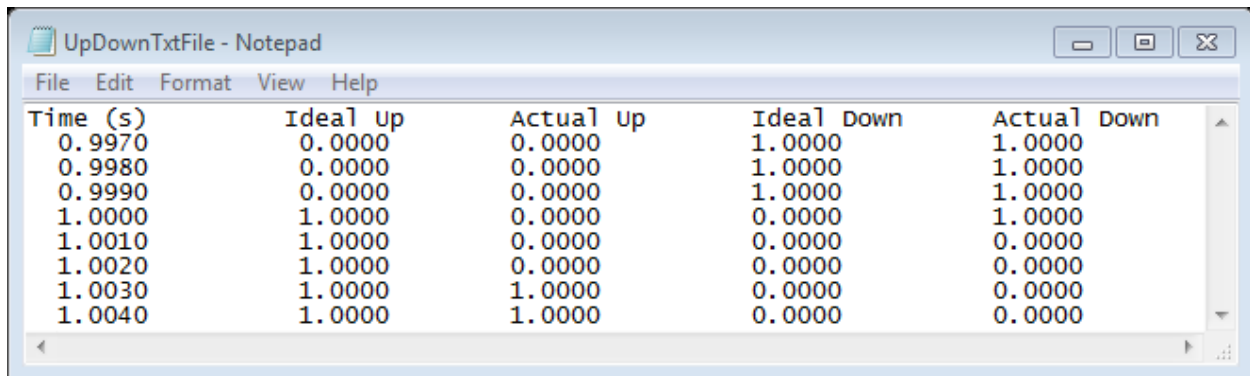


Figure 3.11 Handgrip ergometer data storage flow diagram.

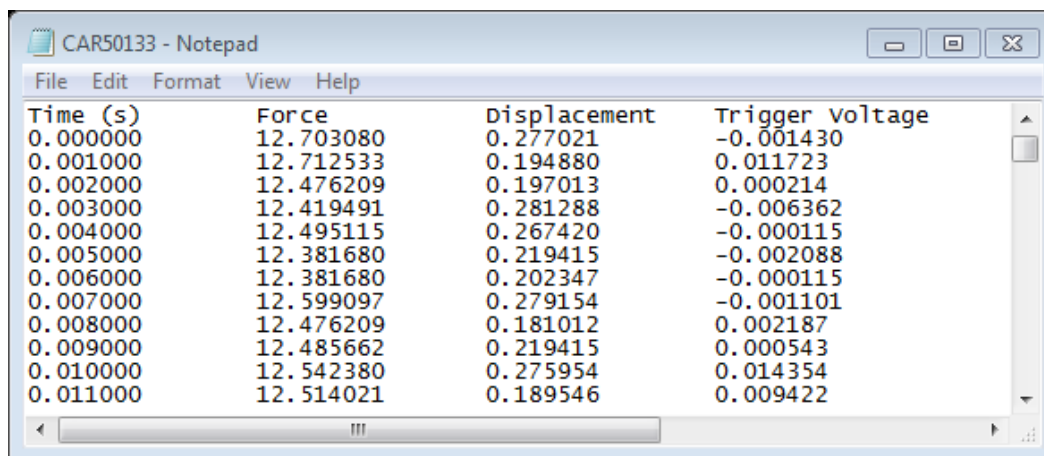
Data received by the contact sensors handled in LabVIEW and saved in their own text file (Figure 3.12). In this file, the time values are aligned with the time values stored in the text file that contains the force, displacement, and work data gathered from the pressure cylinder system and EMG data collected by the system. This allows post-processing software to (a) compare ideal grip movement to actual grip data and (b) correlate grip activity (e.g. rate and duration) to force, displacement, work, and instantaneous power data.



Time (s)	Ideal Up	Actual Up	Ideal Down	Actual Down
0.9970	0.0000	0.0000	1.0000	1.0000
0.9980	0.0000	0.0000	1.0000	1.0000
0.9990	0.0000	0.0000	1.0000	1.0000
1.0000	1.0000	0.0000	0.0000	1.0000
1.0010	1.0000	0.0000	0.0000	0.0000
1.0020	1.0000	0.0000	0.0000	0.0000
1.0030	1.0000	1.0000	0.0000	0.0000
1.0040	1.0000	1.0000	0.0000	0.0000

Figure 3.12 Example text file containing flex sensor data.

As an experiment commences, the raw force and displacement sensor data from the pressure cylinders are digitized and then acquired by the LabVIEW researcher interface, as noted earlier. Prior to display, the LabVIEW VI converts these data into force and displacement, and then it displays the data and saves them in a text file (Figure 3.13).

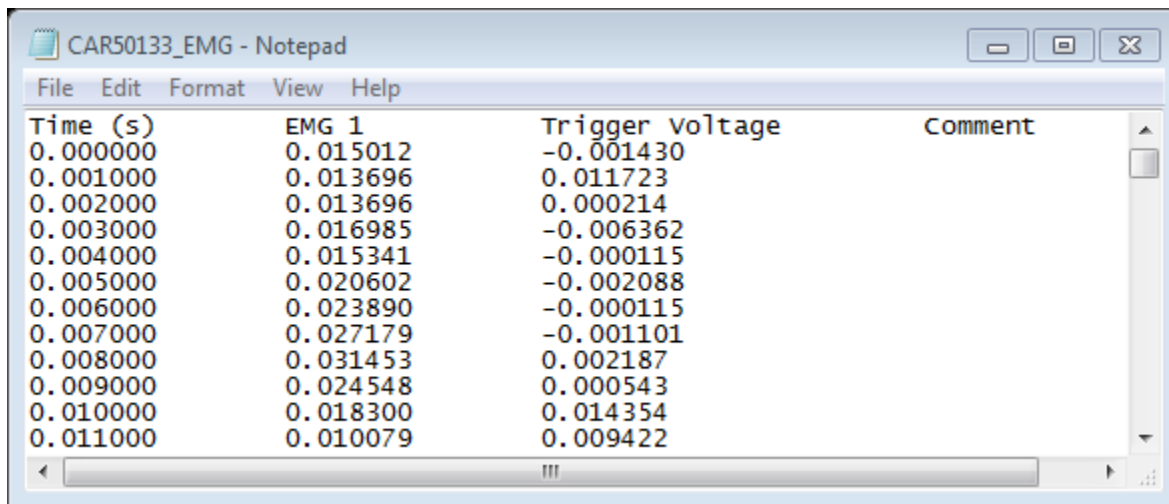


Time (s)	Force	Displacement	Trigger voltage
0.000000	12.703080	0.277021	-0.001430
0.001000	12.712533	0.194880	0.011723
0.002000	12.476209	0.197013	0.000214
0.003000	12.419491	0.281288	-0.006362
0.004000	12.495115	0.267420	-0.000115
0.005000	12.381680	0.219415	-0.002088
0.006000	12.381680	0.202347	-0.000115
0.007000	12.599097	0.279154	-0.001101
0.008000	12.476209	0.181012	0.002187
0.009000	12.485662	0.219415	0.000543
0.010000	12.542380	0.275954	0.014354
0.011000	12.514021	0.189546	0.009422

Figure 3.13 Example text file containing pressure cylinder data.

Additionally the researcher interface brings in the EMG data collected from the Delsys system and time aligns these data with the previous two data documents. The data are saved in a

text file as displayed in Figure 3.14. The additional trigger voltage also allows the researcher to mark key events in the experiment, as seen in Figure 3.13 and Figure 3.14. The researcher simply switches a red flip switch connected to the NI DAQ board (Figure 3.15).



Time (s)	EMG 1	Trigger voltage	Comment
0.000000	0.015012	-0.001430	
0.001000	0.013696	0.011723	
0.002000	0.013696	0.000214	
0.003000	0.016985	-0.006362	
0.004000	0.015341	-0.000115	
0.005000	0.020602	-0.002088	
0.006000	0.023890	-0.000115	
0.007000	0.027179	-0.001101	
0.008000	0.031453	0.002187	
0.009000	0.024548	0.000543	
0.010000	0.018300	0.014354	
0.011000	0.010079	0.009422	

Figure 3.14 Example text file containing EMG data collected from one of the EMG sensor pods (Delsys Trigno wireless system).



Figure 3.15 Image of the physical time marker option for the system.

CHAPTER 4: EMG DATA POST-PROCESSING

Early efforts to perform real-time signal processing in LabVIEW affected the fluidity of the data collection process. Rather than invest resources to optimize these real-time operations, the team decided to post-process the data instead. This chapter summarizes that work.

A. Data Processing Requirements

The following requirements were defined for the post-processing work:

- All data from the various sensors must be time aligned.
- The data processing tool set must be able to load and analyze data acquired at any sampling rate.
- The processing tool set must be able to work for different test scenarios, such as static and ramp workloads.
- EMG data processing will focus on the 30-300 Hz frequency range [20].
- Minimal signal filtering will be used to ensure that the original data remain intact.
- The toolbox must be set up in a manner that allows for easy additions, modifications or updates to the code structure.

The following sections focus on how these processing requirements were addressed.

B. Cylinder: Force, Displacement, & Power Data

As noted in a previous section, the data acquired from the force and displacement sensors are digitized and then forwarded to the LabVIEW researcher interface. Prior to display, the LabVIEW VI converts these data into force and displacement, and then it displays the data and saves them in a text file. Representative force and displacement data for constant-force and increasing-force experiments are depicted in Figure 4.1 and Figure 4.2, respectively.

During post processing, a MATLAB script [15] (created by Wen Song and modified by Thomas Nelson and Dana Gude) converts the force and displacement data to work done by the subject using the relationship

$$Work = Force\ Measured \cdot T \cdot v, \quad (1)$$

where *Force Measured* (Newtons) is the force calculated from the load cell data, *T* (seconds) is the effective duration of each stroke (determined with the help of a peak-detection

algorithm), and v (meters/second) represents the instantaneous speed, determined as the first-order derivative of the displacement, D , in relation to the sampling interval, T_s :

$$v = \frac{D(i) - D(i-1)}{T_s} \quad (2)$$

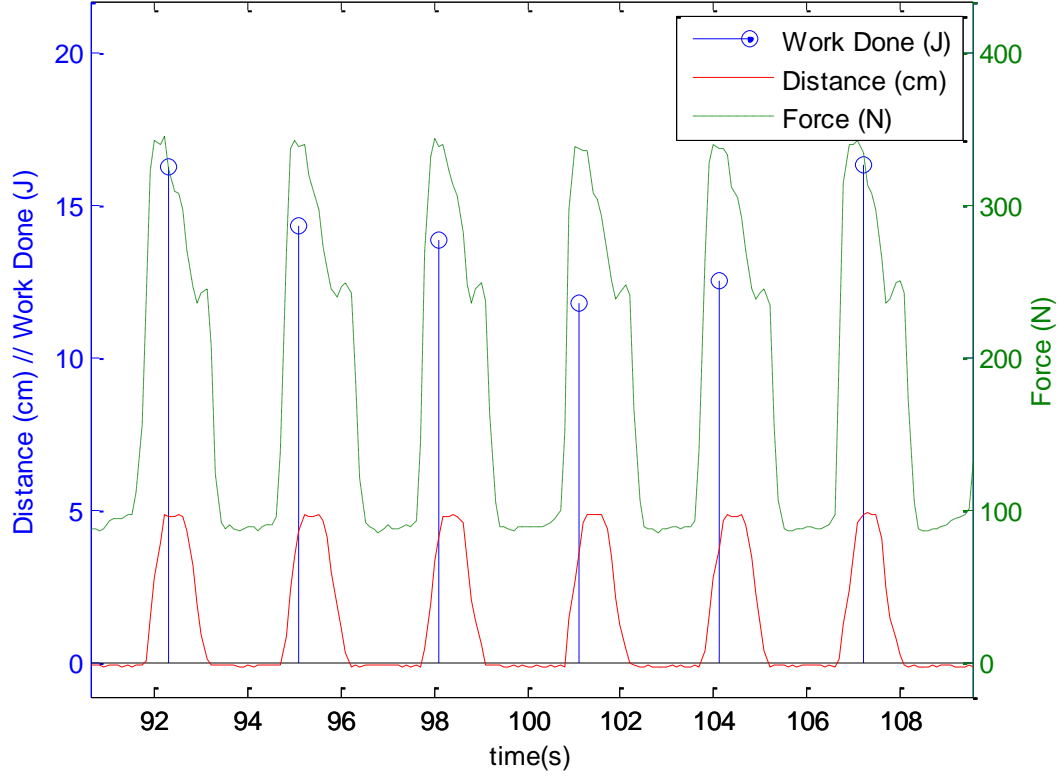


Figure 4.1 Example MATLAB analysis for a constant-force experiment. This example illustrates that the work done for each compression can be variable.

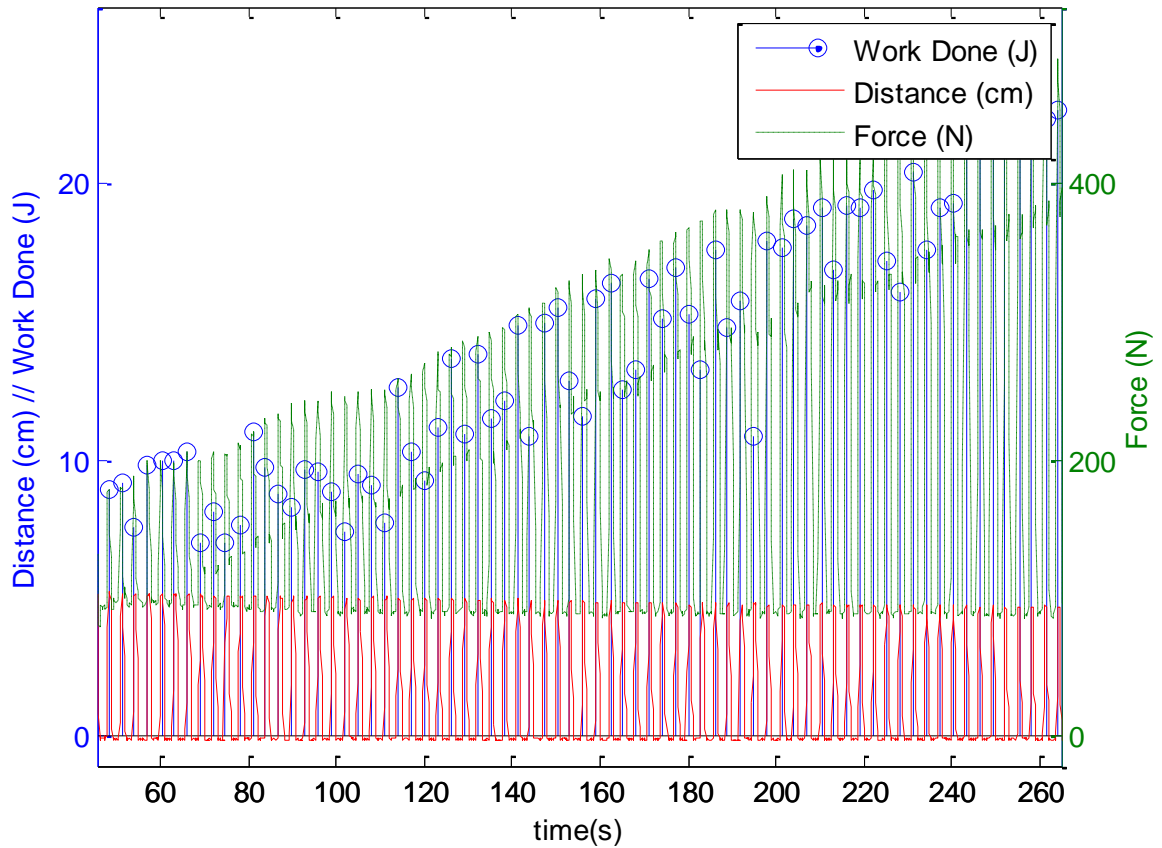


Figure 4.2 Example MATLAB analysis for an increasing-force (ramped) experiment, where the work done gradually increases over time.

C. Contact Sensors: Hold & Release Data

Data received by the contact (flex) sensors are also processed in LabVIEW and saved to a separate text file as discussed in Chapter 3. In this text file, the time values are aligned with the time values stored in the text file that contains the force, displacement, and work data gathered from the pressure cylinder system. This allows post-processing software to (a) compare ideal grip movement to actual grip data and (b) correlate grip activity (e.g., rate and duration) to force, displacement, work, and instantaneous power data.

Representative data for these sensors is depicted in Figure 4.3 along with a corresponding set of instantaneous power calculations. In both data sets (Figure 4.3 A and B), one can see that, at the end of the exercise interval (an approximate range of [140, 160] seconds), the decrease in

power in Figure 4.3 A coincides with delayed subject contractions in Figure 4.3 B, both of which suggest the onset of fatigue.

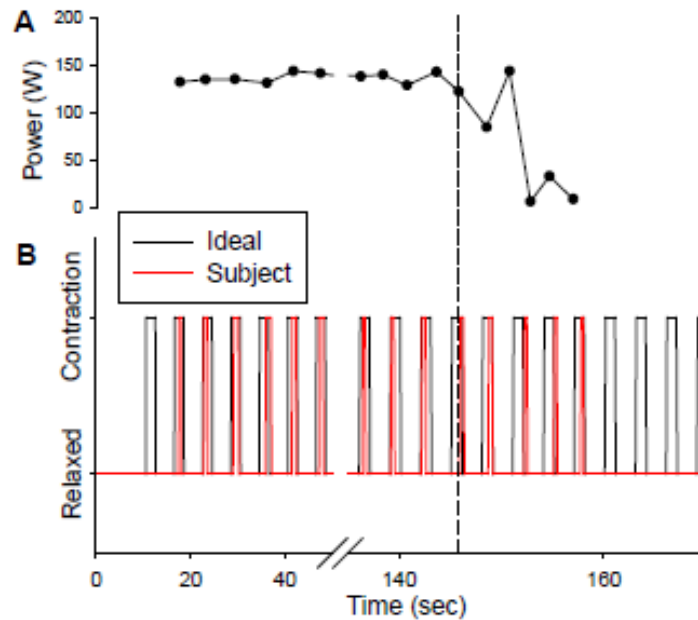


Figure 4.3 Subject data acquired during a constant-work-rate handgrip exercise. **A.** Instantaneous power produced by the subject during the exercise. **B.** Ideal contractions (black line) compared to the actual contractions performed by the subject (red line)

D. KSU EMG Processing Toolbox

The *KSU EMG Processing Toolbox* [21] was created to streamline the processing of data acquired with the hand-forearm ergometer. The toolbox allows the researcher to remove unwanted artifacts from the EMG signal, create an envelope for the EMG data with the use of Clancy's EMG toolbox [16], find start/end times for individual EMG bursts, and calculate four parameters associated with muscle fatigue. These items are described in the following sections.

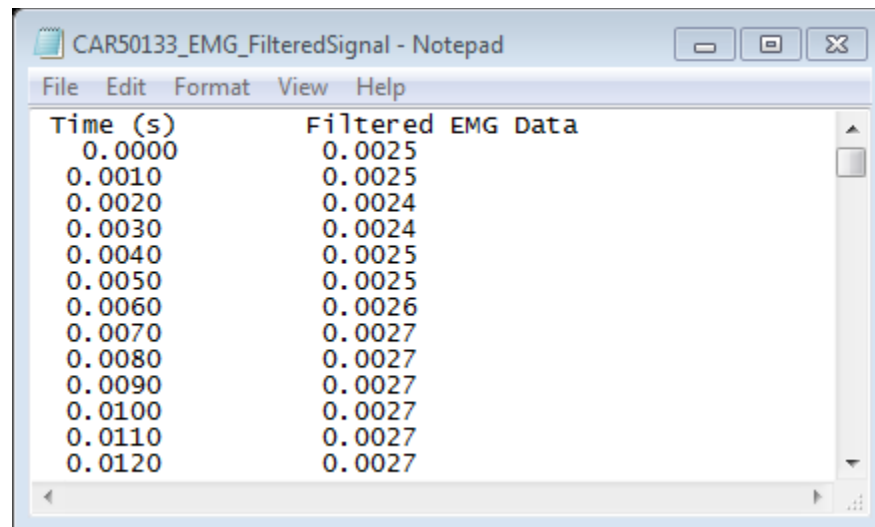
D.1 Data Extraction

EMG data acquired from the human body exhibit multiple types of noise. These include inherent noise, ambient noise, motion artifact noise, and inherent instability of signal noise. This noise results from causative factors (extrinsic, intrinsic), intermediate factors, and deterministic factors [22]. Several methods for minimizing noise were considered. The first method involved

the use of digital filters (e.g., notch, low pass, high pass, and band pass filters). Digital Butterworth filters were initially chosen over analog hardware filters because they are more easily designed and modified. Filter orders and cutoff frequencies were chosen to be consistent with prior EMG processing work [23]. This method, however, created time-alignment issues, so the team migrated to Tom Clancy's EMG processing method, which employs a whitening method and is discussed later in this chapter [16].

D.2 Furthering Processing and Envelope Creation

Typical EMG post-processing methods identify each individual EMG burst, calculate fatigue parameters, and then move to the next burst. With this method, the user calculates parameters from over-filtered data and must know the specific parameters as they process the signals. To remove these constraints and allow for customizable processing of the raw data, a series of MATLAB codes were created. The first code set utilizes Tom Clancy's EMG processing toolbox to create a separate data file that contains a smoothed EMG signal, or EMG envelope, that aligns in time with the raw EMG data (see Figure 4.4 and Figure 4.5). By saving a separate smoothed data file, the researcher now has the option to use the smoothed data or the original data to determine the fatigue parameters.



Time (s)	Filtered EMG Data
0.0000	0.0025
0.0010	0.0025
0.0020	0.0024
0.0030	0.0024
0.0040	0.0025
0.0050	0.0025
0.0060	0.0026
0.0070	0.0027
0.0080	0.0027
0.0090	0.0027
0.0100	0.0027
0.0110	0.0027
0.0120	0.0027

Figure 4.4 Example text file containing the filtered EMG data created by the whitening process defined in [16].

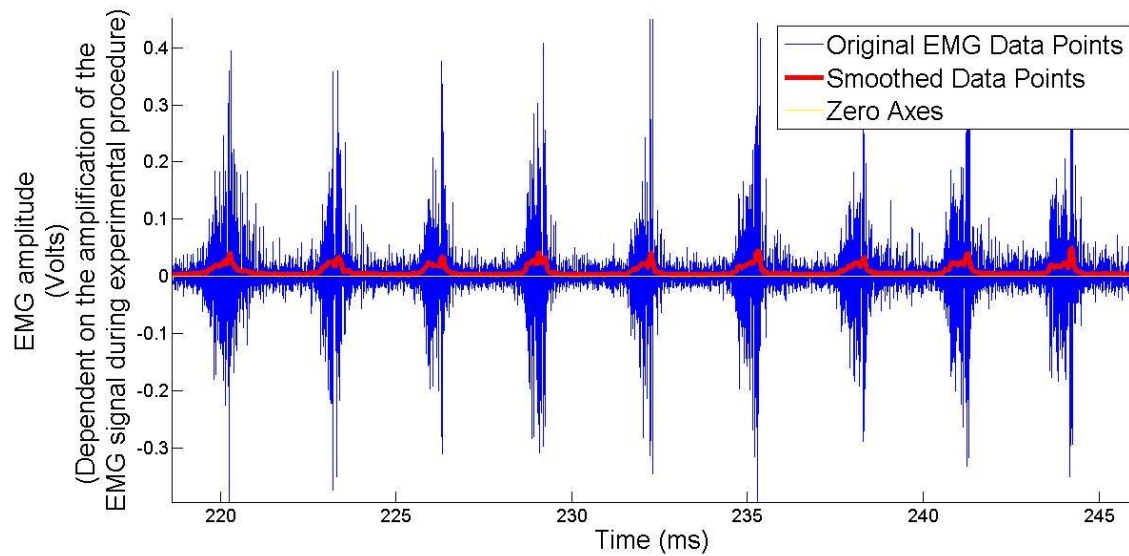


Figure 4.5 Example MATLAB figure created by the toolbox – whitened and smoothed EMG data (red) overlaid on the original EMG data (blue).

D.4 Find Start and End Times

A MATLAB script was created to find each individual EMG burst (using the smoothed data) and then save the array of burst start/end times to a separate file. The identification process involved applying a moving average filter to the smoothed data, followed by a single threshold method for finding the beginnings and ends of the EMG bursts. Clancy’s EMG Amplitude Estimator Toolbox processes EMG data using six stages: “(1) noise rejection/filtering, (2) whitening, (3) multiple-channel combination (including gain scaling), (4) demodulation, (5) smoothing and (6) relinearization. Noise rejection/filtering generally consists of high pass filtering to suppress motion artifact in the raw EMG signal. High pass filtering also removes the offset in the EMG signal which arises from offsets in the recording electronics and A/D converter. Whitening increases the statistical bandwidth [24] of the raw EMG. By temporally uncorrelating the EMG signal, the detection algorithm can operate on each whitened sample separately. Multiple-channel combination is used to combine the information from several electrode recordings made over the same muscle. Demodulation rectifies the whitened EMG and then raises the result to a power. Once demodulated, the information content of the signal changes from the signal standard deviation (prior to demodulation) to the signal mean (raised to a power – after demodulation). Smoothing filters the signal, increasing the signal-to-noise-ratio

(albeit at the expense of adding bias error to the estimate). Finally, relinearization inverts the effect of the power law applied during the demodulation stage, returning the signal to units of EMG amplitude (

Figure 4.6) [25].”

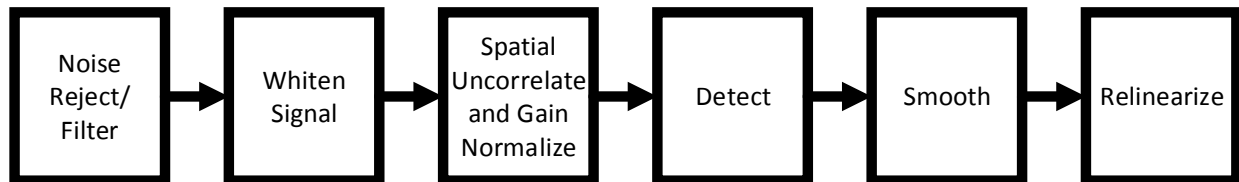


Figure 4.6 Whitening process designed by Clancy for creating the EMG envelope [25].

After the smoothed EMG data are created using Clancy’s EMG estimation toolbox, a double threshold method is applied to the smoothed data to find and store the start and end times of each individual EMG burst. A threshold is determined by averaging the entire EMG data set. The program then looks for the start of the first burst. When the average of an 11-wide sliding window (applied to the smoothed signal) is greater than the threshold and remains greater than the threshold for more than half a second, the program saves the earliest point as a burst start time. After finding a start time, the algorithm looks for an end time in a similar manner. When the sliding window average becomes less than the threshold, the latest value is then stored as a burst end time. Note that the 6th element in the 11-wide window is the recorded value to keep the values and times aligned correctly. This threshold method is a simplified version of the double-threshold method discussed in “A statistical method for the measurement of muscle activation intervals from surface myoelectric signals during gait” by P. Bonato, T. D’Alessio, and M. Knaflitz [26]. As described by M. Reaz in the paper “Techniques of EMG signal analysis: detection, processing, classification and applications,” the double threshold method will produce a higher probability of finding correct detection points and will produce fewer false detection points compared to a single threshold method [22]. The start and end times are saved to a separate text file to be used in further post processing scripts. An example text file can be seen in Figure 4.7. MATLAB also overlays the start and end times on the previously created figure window that displays the raw EMG signal and the data envelope – see Figure 4.8.

Estimated EMG Pulse Times	
Start Pulse Time (s)	End Pulse Time (s)
0.0000	0.0000
5.9320	7.0070
15.3040	16.3050
17.3140	18.3150
54.9550	56.3520
57.3660	58.3670
61.0550	62.0560
64.2490	65.2500
66.8790	67.8910
69.9860	70.9870
72.8270	73.8280
76.0610	77.0620
78.6010	79.7460

Figure 4.7 Example text file containing start/end time values for individual EMG bursts.

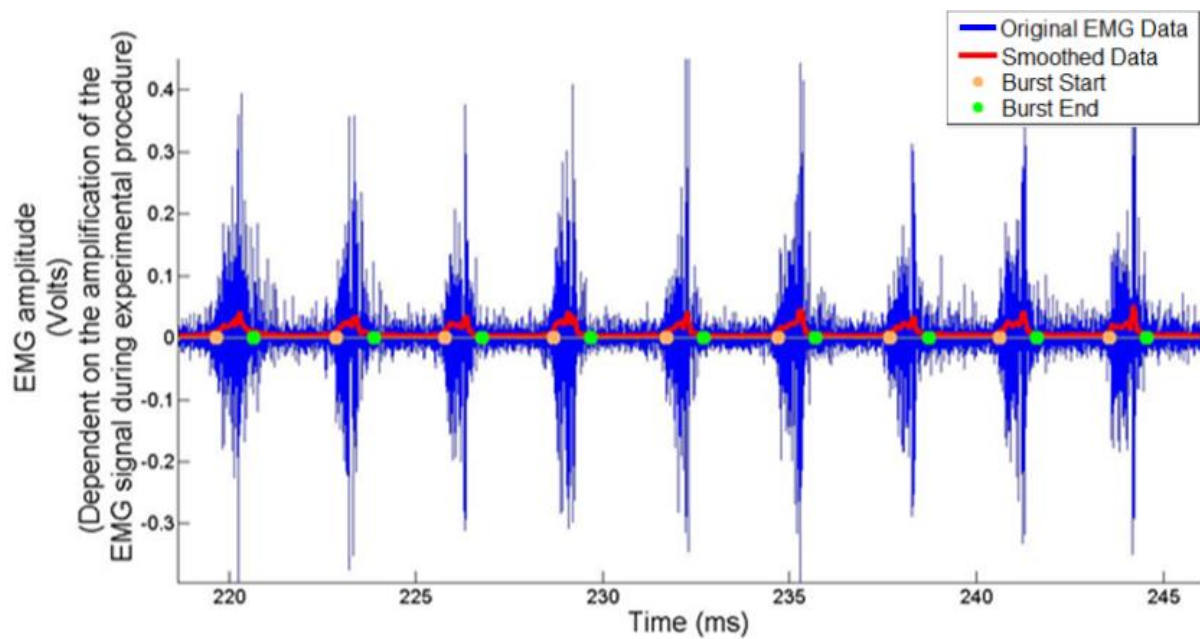


Figure 4.8 Example MATLAB figure. Start (orange dots) and end (green dots) times for the individual EMG bursts are overlaid on the raw EMG data (blue) and the EMG envelope (red).

D.5 RMS, iEMG, Mean Power Frequency & Median Power Frequency

After each EMG burst is identified by start/stop times, the user has the option to choose which fatigue parameter(s) to calculate: the RMS value, the integrated EMG (iEMG) value, the mean power frequency, and/or the median power frequency. The program then digitally filters the data (30-300 Hz pass band [20]) and calculates the requested parameter(s).

D.5.1 Root Mean Square Value

A Root Mean Square (RMS) calculation is typically used “to measure the amplitude of the voluntarily elicited EMG signal [27, 28].” The procedure to calculate the RMS values of the EMG bursts uses the MATLAB function `Ergo_RMS(Burst Time File Set, EMG Data File Set)`. This function requires the file that holds the start and end times for each burst along with a file that holds an EMG signal. The EMG signal can consist of raw data, smoothed data computed with the Clancy whitening method, or any other EMG form as long as the stored data reside in a text file, where a header is followed by a first column that contains time samples and a second column that contains EMG samples. The function first separates the header from the data and removes any DC artifacts from the EMG signal. It then extracts the EMG data segments that exist between the respective start and end times of each burst, storing them to separate arrays. The function then calculates the RMS of each burst using the formula

$$\text{RMS} = \sqrt{\frac{1}{n} \sum_n x_n^2} \quad [28], \quad (3)$$

where n is the index value ($n = 1, 2, 3, \dots$), n is the total number of data points (a constant), and x_n is the value of the signal at a given value of n . The RMS value of each burst is saved in a temporary vector and then stored to a text file similar to the file depicted in Figure 4.9.

RMS of entire EMG file: 0.062105.		
Estimated RMS of each estimated EMG Burst		
Start Burst Time (s)	End Burst Time (s)	RMS
0.0000	0.0000	0.7071
5.9320	7.0070	0.0565
15.3040	16.3050	0.0293
17.3140	18.3150	0.0197
54.9550	56.3520	0.0713
57.3660	58.3670	0.0695
61.0550	62.0560	0.0558
64.2490	65.2500	0.0718
66.8790	67.8910	0.0606
69.9860	70.9870	0.0849
72.8270	73.8280	0.0592
76.0610	77.0620	0.0781
78.6010	79.7460	0.0825
80.7540	82.5050	0.0523
84.7390	85.7490	0.0677
87.7470	88.7880	0.0607

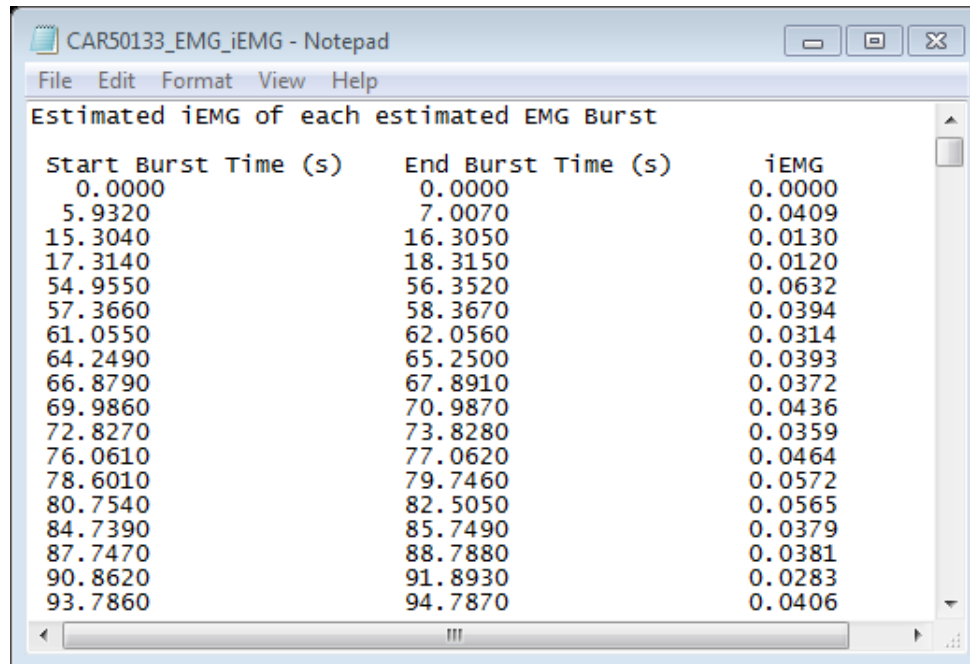
Figure 4.9 Example text file with one subject's start/end burst times and their corresponding calculated RMS values.

D.5.2 Integrated EMG Value

Another important parameter that investigators often use when analyzing EMG data is the integrated EMG (iEMG) value [29]. The MATLAB function `Ergo_iEMG(Burst Time File Set, EMG Data File Set)` provides this service by integrating the EMG signal over each burst. This calculation is similar to the RMS calculation and is used in much the same way; both methods give similar, if not the same, analysis patterns, which can be seen in the results in Chapter 5. The function requires the file that holds the start and end times for each burst along with a file that holds an EMG signal. As before, the EMG signal can consist of raw data, smoothed data computed with the Clancy whitening method, or any other EMG form as long as the stored data reside in a text file, where a header is followed by a first column that contains time samples and a second column that contains EMG samples. The function first separates the header from the data and removes any DC artifacts from the EMG signal. It then extracts the EMG data segments that exist between the respective start and end times of each burst, storing them to separate arrays. The function computes the iEMG value of each burst using the formula

$$iEMG[|m(t)|] = \int_0^t |m(t)| dt \quad [29]. \quad (4)$$

where $|m(t)|$ represents the absolute value of the time-dependent EMG data within a burst. The iEMG value of each burst is saved in a temporary vector and then stored to a text file similar to the file depicted in Figure 4.10.



Start Burst Time (s)	End Burst Time (s)	iEMG
0.0000	0.0000	0.0000
5.9320	7.0070	0.0409
15.3040	16.3050	0.0130
17.3140	18.3150	0.0120
54.9550	56.3520	0.0632
57.3660	58.3670	0.0394
61.0550	62.0560	0.0314
64.2490	65.2500	0.0393
66.8790	67.8910	0.0372
69.9860	70.9870	0.0436
72.8270	73.8280	0.0359
76.0610	77.0620	0.0464
78.6010	79.7460	0.0572
80.7540	82.5050	0.0565
84.7390	85.7490	0.0379
87.7470	88.7880	0.0381
90.8620	91.8930	0.0283
93.7860	94.7870	0.0406

Figure 4.10 Example text file containing EMG burst start/end times and the corresponding integrated EMG values.

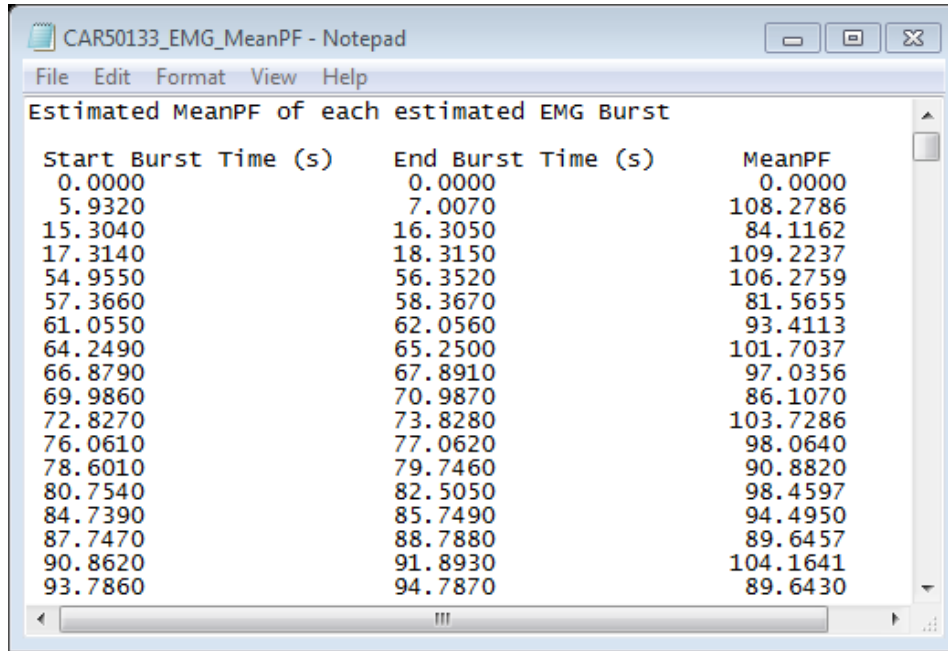
D.5.3 Mean Power Frequency

The mean power frequency and median power frequency are both sensitive to muscle fatigue and represent changes in the shape of an EMG's frequency-domain spectrum [28, 30]. Both of these parameters decrease as a muscle fatigues [28, 31]. The MATLAB function `Ergo_MeanPF(Burst Time File Set, EMG Data File Set)` calculates the mean power frequency of each individual EMG burst. The function requires the file that holds the start and end times for each burst along with a file that holds an EMG signal. As before, the EMG signal can consist of raw data, smoothed data computed with the Clancy whitening method, or any other EMG form as long as the stored data reside in a text file, where a header is followed by a first column that contains time samples and a second column that contains EMG samples. The function first separates the header from the data and removes any DC artifacts from the EMG signal. It then extracts the EMG data segments that exist between the respective start and end times of each burst, storing them to separate arrays.

The mean power frequency of the EMG signal “is the average frequency of the power spectrum and is defined as its first-order moment:

$$\text{mean power frequency} = \frac{\int_0^{\infty} f P(f) df}{\int_0^{\infty} P(f) df} \text{ „ } [20, 30]. \quad (5)$$

where $p(f)$ represents the power spectral density of the EMG burst and f represents frequency in Hz. Because artifacts occur in the frequency band of the raw data, the frequency range is usually limited to 30-300 Hz for mean frequency calculations [20]. In this program, the MATLAB Fast Fourier Transform is used to convert the time-domain EMG burst data into frequency-domain coefficients. The mean frequency value for each burst is saved to a vector and then stored to a text file similar to Figure 4.11.



Start Burst Time (s)	End Burst Time (s)	MeanPF
0.0000	0.0000	0.0000
5.9320	7.0070	108.2786
15.3040	16.3050	84.1162
17.3140	18.3150	109.2237
54.9550	56.3520	106.2759
57.3660	58.3670	81.5655
61.0550	62.0560	93.4113
64.2490	65.2500	101.7037
66.8790	67.8910	97.0356
69.9860	70.9870	86.1070
72.8270	73.8280	103.7286
76.0610	77.0620	98.0640
78.6010	79.7460	90.8820
80.7540	82.5050	98.4597
84.7390	85.7490	94.4950
87.7470	88.7880	89.6457
90.8620	91.8930	104.1641
93.7860	94.7870	89.6430

Figure 4.11 Example text file containing EMG burst start/stop times and the corresponding mean power frequencies.

Typically, the mean power frequency is used to determine the fatigue status for a specific muscle. Muscle fatigue can often be determined when there is a large enough percentage change in the value of the mean power frequency, because as a person fatigues, the value decreases.

D.5.4 Median Power Frequency

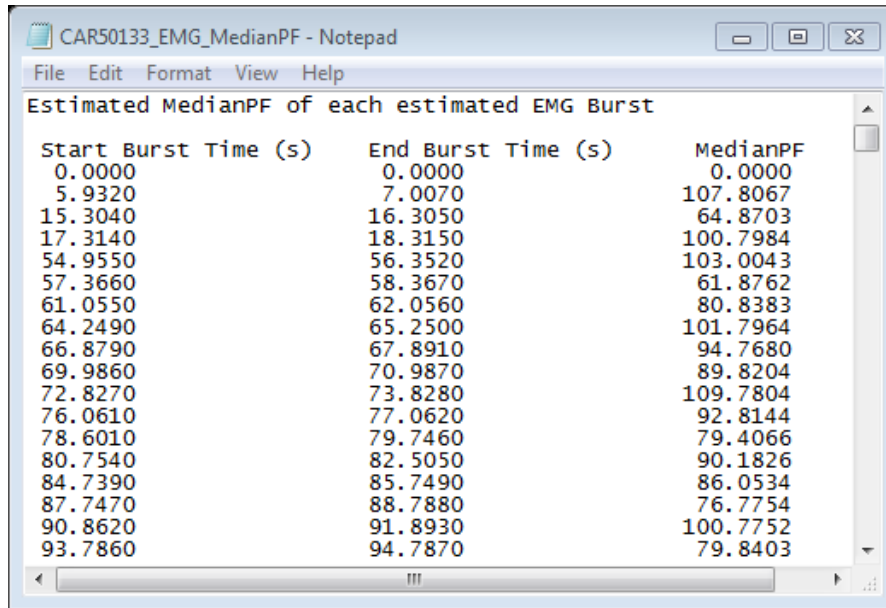
The median power frequency is also used to analyze changes in the shape of an EMG’s frequency-domain spectrum; the parameter is similar to the mean power frequency in terms of

how it is used and how it behaves as a muscle fatigues [28]. The median power frequency is often used instead of the mean power frequency because it is “less sensitive to noise, less sensitive to signal aliasing, and in most cases more sensitive to the biochemical and physiological processes that occur within the muscles during sustained contractions [27].”

“The median frequency is the frequency value that separates the power spectrum in two parts of equal energy

$$\int_{f_1}^{F_{median}} PS(f)df = \int_{F_{median}}^{f_2} PS(f)df \quad (6)$$

where $PS(f)$ is the sEMG (surface EMG) power spectrum that is calculated using a Fourier transform, and f_1 and f_2 (in Hz) determine the bandwidth of the surface electromyograph [28].” In this specific algorithm, f_1 was set to 30 Hz and f_2 was set to 300 Hz as suggested by [20]. As with the mean power frequency calculations, the MATLAB Fast Fourier Transform is used to convert the time-domain EMG burst data into frequency-domain coefficients. The data are then saved to a text file similar to the one in Figure 4.12.



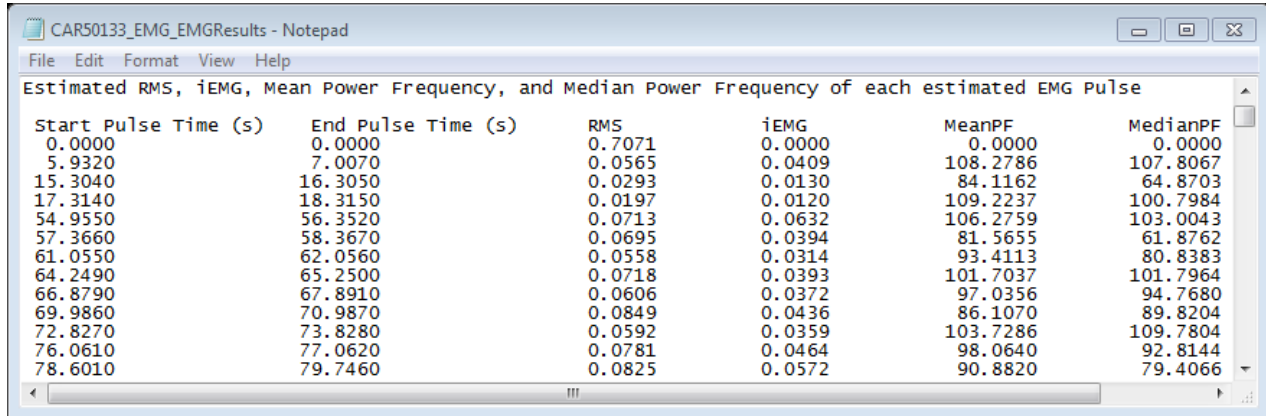
Start Burst Time (s)	End Burst Time (s)	MedianPF
0.0000	0.0000	0.0000
5.9320	7.0070	107.8067
15.3040	16.3050	64.8703
17.3140	18.3150	100.7984
54.9550	56.3520	103.0043
57.3660	58.3670	61.8762
61.0550	62.0560	80.8383
64.2490	65.2500	101.7964
66.8790	67.8910	94.7680
69.9860	70.9870	89.8204
72.8270	73.8280	109.7804
76.0610	77.0620	92.8144
78.6010	79.7460	79.4066
80.7540	82.5050	90.1826
84.7390	85.7490	86.0534
87.7470	88.7880	76.7754
90.8620	91.8930	100.7752
93.7860	94.7870	79.8403

Figure 4.12 Example text file containing EMG burst start/stop times and the corresponding median power frequencies.

D.5.5 Combination of RMS, iEMG, Mean Power Frequency, and Median Power Frequency

A combination of the four parameters can be useful to better understand muscle activity. Thus, an EMG toolbox function was created to allow the investigator to calculate all four

parameters using one function call: `Ergo_EMG_toolbox(Burst Time File Set, EMG Data File Set)`. The function requires the same two files as the previous functions. After all four calculations are performed; the parameters are saved to one file as in Figure 4.13.



Start Pulse Time (s)	End Pulse Time (s)	RMS	iEMG	MeanPF	MedianPF
0.0000	0.0000	0.7071	0.0000	0.0000	0.0000
5.9320	7.0070	0.0565	0.0409	108.2786	107.8067
15.3040	16.3050	0.0293	0.0130	84.1162	64.8703
17.3140	18.3150	0.0197	0.0120	109.2237	100.7984
54.9550	56.3520	0.0713	0.0632	106.2759	103.0043
57.3660	58.3670	0.0695	0.0394	81.5655	61.8762
61.0550	62.0560	0.0558	0.0314	93.4113	80.8383
64.2490	65.2500	0.0718	0.0393	101.7037	101.7964
66.8790	67.8910	0.0606	0.0372	97.0356	94.7680
69.9860	70.9870	0.0849	0.0436	86.1070	89.8204
72.8270	73.8280	0.0592	0.0359	103.7286	109.7804
76.0610	77.0620	0.0781	0.0464	98.0640	92.8144
78.6010	79.7460	0.0825	0.0572	90.8820	79.4066

Figure 4.13 Example text file containing all of the parameters calculated by the EMG toolbox. The file contains the start/end times, the root mean square value, the integrated EMG value, the mean power frequency, and the median power frequency for each burst.

D.6 Separation of Data Using a Trigger Threshold Value

While the toolbox works for most experiments, it became apparent that some data sets are just too large to process and even more cumbersome to manage. A code was therefore needed to split the larger files into smaller, more manageable files. The team decided that the code should split the data at the rows demarcated by a set of triggers (time markers).

The data-splitting code requires an input file where the first column is time, the second column is the EMG signal (or any other data signal), and the third column is the trigger value. The trigger column may be manually entered or created by the LabVIEW interface during the experiment. The algorithm copies the data row by row until it reaches the time value corresponding to the trigger set by the user. It then saves that matrix of data to a text file, closes the file, and continues to work through the data until it reaches the next trigger. These data are then saved to a separate text file. The process is continued until the entire data file has been read and split into separate text files. Data analysis, as described in the previous sections, can then be performed on the smaller data sets.

D.7 Non-Traditional Processing: Movie Verification Code

EMG data are traditionally analyzed in a manner similar to the method in the previous sections. One goal of this project was to begin to look at potentially different methods for analyzing/displaying EMG data as well as new parameters that might be beneficial to the researcher. One step toward this goal was to create a movie that would allow the researcher to visualize changes in EMG burst shape as a subject's muscles fatigue. To accomplish this, a MATLAB function was created that would display burst information in a given movie frame and then update that frame with new burst information as it arrives. Information of interest includes the time-domain burst, the magnitude of the frequency spectrum, the frequency power spectrum, the RMS value, the iEMG value, the mean power frequency, and the median power frequency. An example frame from a movie is contained in Figure 4.14.

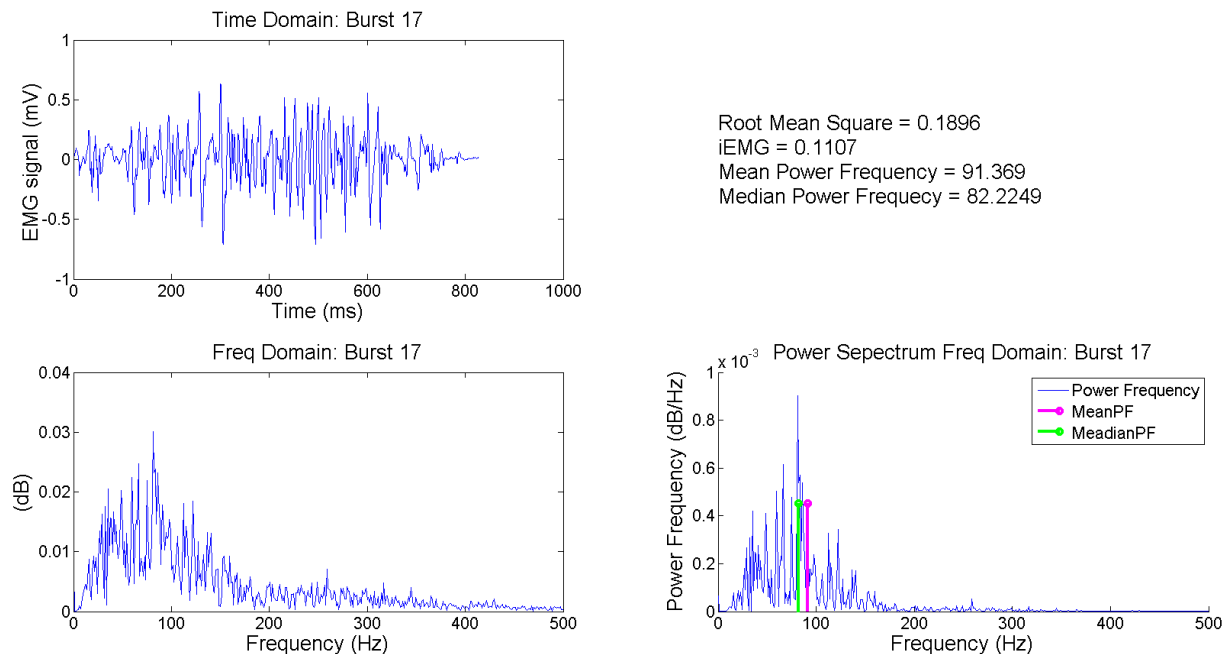


Figure 4.14 An example screen shot of the burst information displayed in one frame of a MATLAB movie clip.

As can be seen in the figure above, the user can visualize all of the parameters calculated for a single burst at the same time. The isolated time-domain burst is in the upper left corner, the magnitude of its frequency spectrum is in the lower left corner, its power spectrum is in the lower right corner, and the four fatigue parameters are in the upper right corner.

CHAPTER 5: RESULTS

The LabVIEW interfaces and MATLAB scripts were utilized in the Kansas State Human Exercise Physiology Laboratory to determine the usefulness of these data acquisition and post-processing tools with regard to studying muscle fatigue. The results and analyses included in this chapter were primarily provided by Ryan Broxterman and Dr. Thomas Barstow.

The Human Exercise Physiology Laboratory tested eight subjects in two types of muscle contraction scenarios. Both studies used the hand-forearm ergometer system and kept the concentric contractions the same for all subjects in each of the individual trials. The muscle investigated was the flexor digitorum superficialis and was kept the same for all subjects as well. The first study used a 20% duty cycle, where a 20% duty cycle is defined as a subject squeezing the bars for 20% of an interval followed by an immediate release. Thus, the subject's forearm muscles would have longer timespans to rest in between contractions. The second study employed a 50% duty cycle – a more natural squeeze and release sequence where the subject squeezes the two bars together and then slowly releases the bars. This type of release results in longer muscle contractions and shorter resting times. All studies were performed until each subject was no longer able to continue due to fatigue. The results of these two studies are discussed in the following sections.

A. Root Mean Square and Integrated EMG Results

The data collected from the experiments were processed with the Ergometer EMG toolbox. From their calculations, the individuals in the Human Exercise Physiology Laboratory concluded that both the RMS and iEMG values provided by the toolbox were able to successfully demonstrate an increase in the number of motor units being used by the forearm. As discussed in Chapter 4, the RMS and iEMG values are excellent parameters for tracking EMG signal changes in the time domain with respect to changes in motor unit recruitment [32]. In the first experiment, where a 20% duty cycle was used, one sees little increase in the RMS and iEMG values as the experiment progresses. This suggests that the motor units were recruited early on in the exercise and were all that were needed to sustain the power needs of the exercise (white dots in Figure 5.1 and Figure 5.2) [31].

In the second experiment, where a 50% duty cycle was used, each muscle contraction was held for a longer time. Thus, as the experiment progressed, more motor units in the forearms had to be recruited to complete the exercise (black dots in Figure 5.1 and Figure 5.2). (Note: In the figure, the average of each data point is displayed with a black or white dot, and the standard deviation of each data is displayed with the extended bars.) Note from the graphs that the 50% duty cycle created a much shorter time to fatigue when compared to the 20% duty cycle

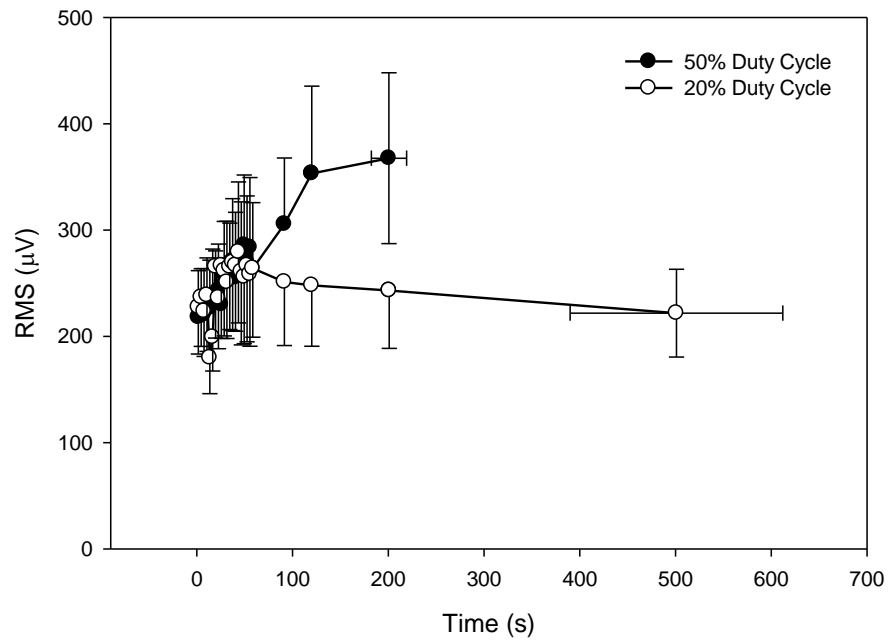


Figure 5.1 Changes in RMS value calculated using the toolbox and graphed in SigmaPlot.

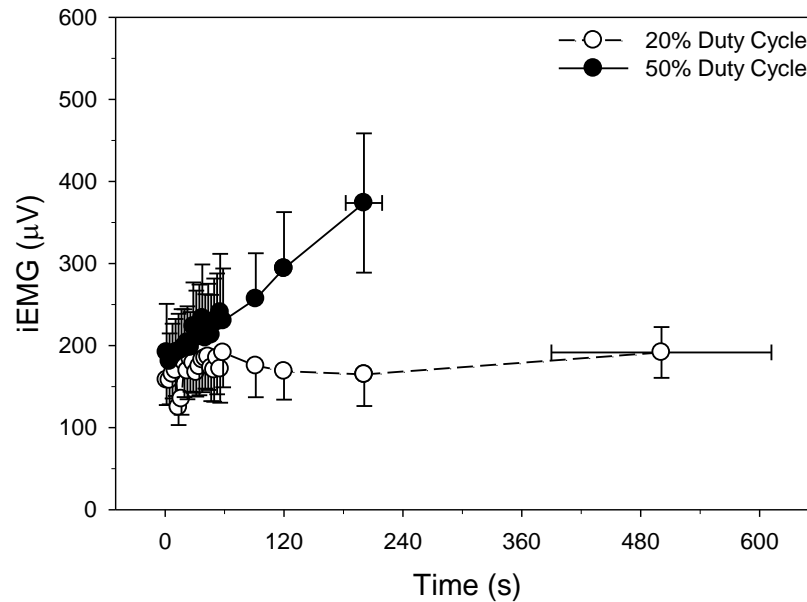


Figure 5.2 Changes in the integrated EMG value calculated using the toolbox and graphed in SigmaPlot.

B. Mean Power Frequency and Median Power Frequency

The same subject data were analyzed with the mean power frequency and median power frequency calculation algorithms in the toolbox. As discussed in Chapter 4, the mean and median calculations are sensitive to fatigue. As the subject fatigues, the mean and median values are expected to shift to lower frequencies as the muscle action potentials begin to spread out. This frequency decrease can be seen in the mean and median power frequencies in Figure 5.3 and Figure 5.4. The calculation results displayed in these figures indicate that the longer duty cycle of 50%, when compared to the shorter duty cycle of 20%, caused more of a decrease in the calculated mean and median frequencies.

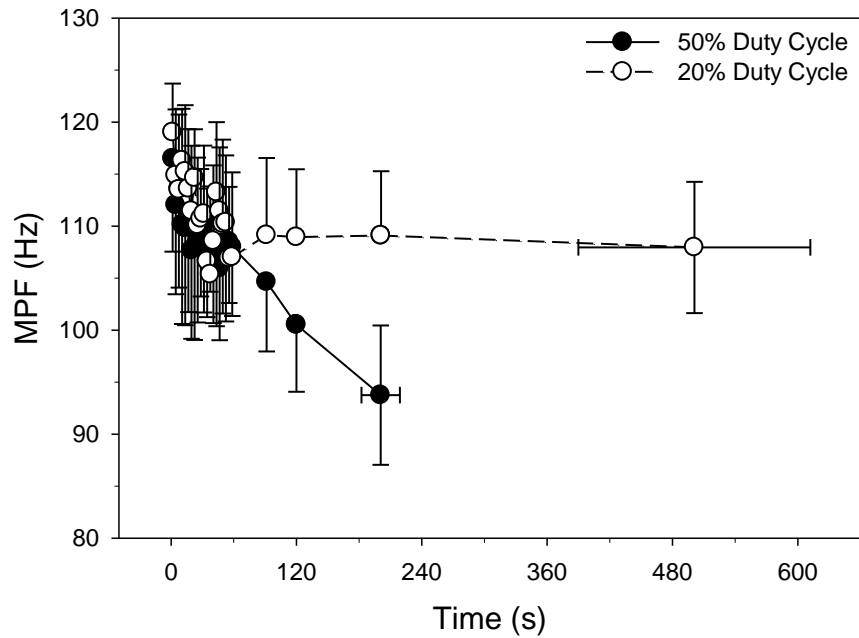


Figure 5.3 Changes in the mean power frequency calculated using the toolbox and graphed in SigmaPlot.

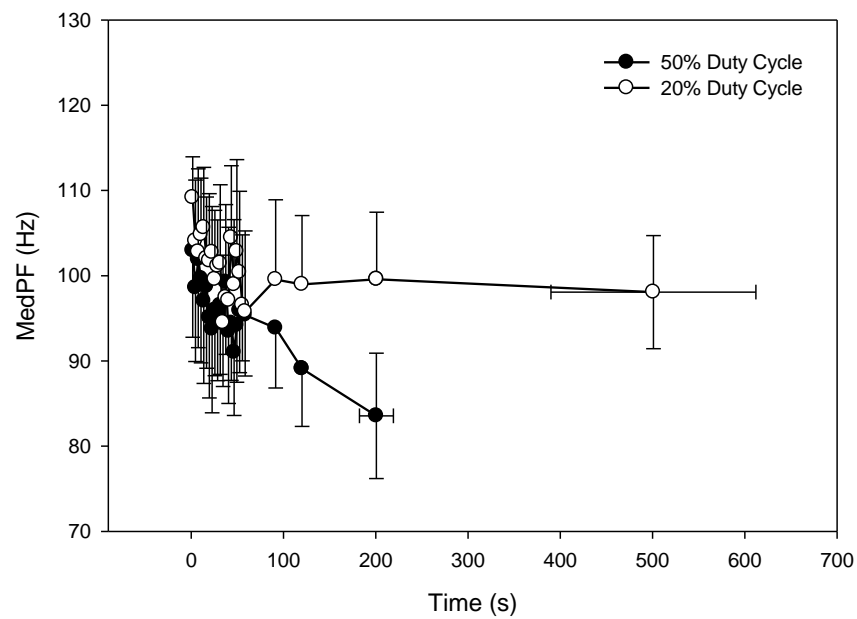


Figure 5.4 Changes in the median power frequency calculated using the toolbox and graphed in SigmaPlot.

CHAPTER 6: CONCLUSIONS AND FUTURE WORK

A. Conclusion

This thesis presented an automated tool set to be used with the KSU Human Exercise Physiology Laboratory's hand-forearm ergometer system, where the goal is to aid the investigation of muscle fatigue in the forearms within the context of the human performance grant provided by NASA [21]. The tool set automates tasks previously managed manually. It provides the researcher with a centralized control interface with the option of a separate subject interface. The interface also offers the flexibility to add and remove sensors to the system, such as pressure cylinder force sensors, squeeze/release pressure sensors, and EMG sensors. The interface environment chosen (LabVIEW) is easily learned and modified, thus making the tool set easy for future researchers to maintain and update.

For ease of use and more accurate testing, many of the manually controlled operations of the experiment were automated through the researcher's central interface. These upgrades included a digitized metronome with the option of changing the audio sounds and tempo, and a digitized control for the pressure cylinders to allow for quicker and more accurate pressure increases and decreases during an experiment.

Finally, in order to make the upgrades useful to the researcher, an EMG data post-processing tool set was created. The tool set focuses on an analysis of the work done by the subject (pressure cylinder data) and an EMG analysis toolbox for looking at fatigue using root mean square, integrated EMG, mean power frequency, and median power frequency parameters.

With these upgrades, the Human Exercise Physiology Laboratory was able to more consistently collect data and perform post processing procedures.

B. Future Work

Several upgrades are planned to the system to make the toolbox more versatile and complete. The first upgrade to the system should be a LabVIEW implementation of the post-processing routines to allow for on-screen, real-time updates during an experiment. This should include an improved burst detection method that does not need the full data set to isolate the parameters relevant to the individual EMG bursts. The second addition would be a MATLAB function that would allow the user to identify the functions they want the post-processing scripts to run, so that

the user would only have to type one MATLAB function line and be able to do a full processing sequence. The third upgrade should be an improved burst detection algorithm. Currently, the burst detection algorithm works for a periodic burst set but has difficulty with aperiodic burst sets. The final upgrade should be the implementation of alternative methods for analyzing EMG signals both in the time and frequency domains outside of the traditional RMS, iEMG, mean power frequency, and median power frequency parameters. This might lead to new parameters or techniques for identifying fatigue and its onset.

CHAPTER 7: REFERENCES

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